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Alós-Ferrer, Carlos ; Garagnani, Michele

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DOI: https://doi.org/10.1016/j.econlet.2020.109672

Posted at the Zurich Open Repository and Archive, University of Zurich
ZORA URL: https://doi.org/10.5167/uzh-194132
Journal Article
Published Version

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Originally published at:
Alós-Ferrer, Carlos; Garagnani, Michele (2021). Choice consistency and strength of preference. Economics Letters, 198(109672):online.
DOI: https://doi.org/10.1016/j.econlet.2020.109672

Economics Letters 198 (2021) 109672

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Choice consistency and strength of preference

Carlos Alós-Ferrer *, Michele Garagnani

Zurich Center for Neuroeconomics (ZNE), Department of Economics, University of Zurich, Blümlisalpstrasse 10, 8006 Zurich, Switzerland

A R T I C L E   I N F O

Article history:
Received 16 July 2020
Received in revised form 19 November 2020
Accepted 21 November 2020
Available online 24 November 2020

JEL classification:
D01
D81
D91

Keywords:
Choice consistency
Stochastic choice
Strength of preference

A B S T R A C T

Even when presented with the same choices multiple times, humans often make different decisions. We re-analyze data from five experiments using repeated choices in the domain of risky and intertemporal choices and show that choice consistency is directly linked to cardinal differences in independently-estimated utilities. Strength of preference is monotonically related to choice consistency, with choices being more inconsistent when the alternatives are more similar in preference terms.

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> "Common experience suggests, and experiment confirms, that a person does not always make the same choice when faced with the same options, even when the circumstances of choice seem in all relevant aspects to be the same".
>
> [Davidson and Marschak (1959)]

1. Introduction

Research in stochastic choice has shown that human beings often make different choices even when repeatedly confronted with the same set of options (e.g., Tversky, 1969; Hey and Orme, 1994; Ballinger and Wilcox, 1997; Conte et al., 2011). There is, however, no universally-accepted view on the determinants of choice inconsistency. Hey (2001) found that consistency improves with repetition for some subjects, but remains low for others. Andersson et al. (2016) suggest that higher inconsistency might be associated with lower cognitive ability and, as a result, bias estimates of the relation between the latter and risk aversion. Agranov and Ortoleva (2017) argue that one factor behind choice inconsistency might be idiosyncratic preferences for randomization.

Choice inconsistencies are in agreement with discrete choice and random utility models as pioneered by Marschak (1960) and McFadden (1974, 2001). In those models, underlying utility differences for a pair (x, y) are perturbed by a noise term ε and actual choice follows the realization $u(x) - u(y) + \varepsilon$. As a consequence, the probability of a choice which goes against the underlying utility difference is larger if $u(x) - u(y)$ is closer to zero. It follows immediately that consistency in repeated choices should be higher in the latter case. This is also an implication of the choice model of Luce (1959), because it can be recast as a random utility model (Anderson et al., 1992, Chapter 1).

Inconsistent choice is also in agreement with evidence dating back to Fechner (1860). A robust finding from psychophysics is that, in discrimination tasks, errors are more frequent when stimuli are more similar, a fact usually referred to as a "psychometric relation" (e.g., Dashiell, 1937; Laming, 1985; Wichmann and Hill, 2001). This is often taken as evidence that decisions might derive from noisy processes of internal evidence accumulation in the human brain Shadlen and Kiani (2013) and Fudenberg et al. (2018). Thus, choices involving more similar alternatives (hence harder) should lead to higher inconsistency if repeated. However, in this literature, the similarity across stimuli is either objective (length, weight, brightness) or based on self-reported ratings (liking). In contrast, a given, objective scale is rarely given in economics, as underlying preferences need to be revealed or estimated. The difference has been discussed in Alós-Ferrer and Garagnani (2018).

In this work, we directly test the hypothesis that economic decisions where expected utility differences are closer to zero result in a higher degree of inconsistency. We re-analyze five

* Corresponding author.
E-mail addresses: carlos.alos-ferrer@econ.uzh.ch (C. Alós-Ferrer), michele.garagnani@econ.uzh.ch (M. Garagnani).

https://doi.org/10.1016/j.econlet.2020.109672
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different datasets (four with choices under risk and one with intertemporal choices) where subjects were repeatedly confronted with the same binary choices and provide robust evidence of a "strength of preference" result in choice consistency: (repeated) choices are more inconsistent when alternatives are "closer to indifference". Hence, our approach relates individual-level utilities and observed choice consistency.

We employ an out-of-sample estimation procedure, where the utility difference for a given choice pair is estimated from decisions which do not include that choice pair. This is important, because standard utility estimation through random utility models (McFadden, 2001) assumes a psychometric relation, and hence a within-sample fitting approach might produce spurious results.

2. The datasets

Hey (2001), whose dataset was also used by Moffatt (2005) and Conte et al. (2011), investigated whether deviations from Expected Utility theory decay with repetition ($N = 53$, 100 lottery choices, 5 repetitions on different days). Davis-Stober et al. (2015) studied whether lottery choices ($N = 60$ subjects, 20 lottery choices, 24 repetitions) could be represented by utility functions or not. For comparability, we exclude a within-subject treatment which used time pressure (results are qualitatively unchanged if we include it). Agranov and Ortoleva (2017) investigated whether decision makers display a preference for deliberate randomization ($N = 80$, 10 lottery choices, 4 repetitions). We exclude a second treatment where subjects were made aware of the repetition. McCausland et al. (2020) evaluated random utility models and found that a large majority of the subjects behaved in alignment with those ($N = 141$, 10 lottery choices, 6 repetitions intermixed with other choices). Last, He et al. (2019) test the predictive power of exponential and hyperbolic discounting (we rely on their Experiments 1–2: $N = 89$, 60 binary choices, 4 repetitions).

The datasets were collected to answer different questions and represent a variety of decision environments with different implementations and characteristics. In isolation, each dataset might require a discussion of their design and implementation particularities. Taken together, they deliver robust evidence of the effect we discuss.

3. Utility estimation

To implement an out-of-sample analysis, we split each dataset in two sets of decisions, each one containing all the repetitions of half of the choice pairs. We then estimate utility parameters for each subject and use the ones derived from odd-numbered choice pairs to evaluate the utility differences of even-numbered ones, and vice versa. This avoids using the same decisions for estimation and for testing. Our results do not change with different out-of-sample approaches, as e.g. using an initial block of observations for the estimation, or a leave-one-out procedure.

For the first four datasets, we estimate individual-level risk attitudes with a standard additive random utility model (e.g., McFadden, 2001), following well-established procedures (e.g. Moffatt, 2015). We consider normally-distributed errors and assume a normalized constant absolute risk aversion (CARA) function as in Conte et al. (2011),

$$u(x) = \begin{cases} \frac{1-\exp(-rx)}{1-\exp(-rx_{\max})}, & \text{if } r \neq 0 \\ \frac{x}{x_{\max}}, & \text{if } r = 0, \end{cases}$$

where $x_{\max}$ is the upper bound of the outcome variable x. All results remain qualitatively unchanged assuming a constant relative risk aversion utility function instead, or implementing a random parameter model (Loomes and Sugden, 1998), which postulates a different noise specification.

For the dataset of He et al. (2019), we use the same procedure but, following those authors, assume a two-parameter hyperbolic discounting model (Loewenstein and Prelec, 1992). Assuming quasi-hyperbolic discounting (Laibson, 1997) instead does not qualitatively change the results.

4. Results

Consistency is defined as choosing the same option across all repetitions. To make the results comparable, in each dataset utility distances were normalized to have a maximum value of one. Fig. 1 depicts the proportion of inconsistent choices as a function of estimated utility differences for all five datasets. For ease of presentation, the figure uses a binning procedure over the x-axis, with bins of width 0.01. That is, the y-value of each point represents an average for all observations with utility differences in the same bin.[1]

Table 1 displays panel Probit regressions on the likelihood of a consistent choice for the same datasets. That is, the dependent variable is a dummy taking the value one if the subject chose the same option for all instances of the corresponding choice pair. All datasets display the expected pattern, with smaller utility differences resulting in more inconsistencies, as reflected by an inverted U-shaped relation between choice inconsistency and expected utility differences. Inconsistencies are maximized around zero, and become gradually smaller in magnitude as those differences increase. All regressions indicate higher consistency for easier choices, as measured by utility differences. The effect is observed at the 1% significance level in all five datasets.[2] The magnitudes of the coefficients are also comparable, except for Davis-Stober et al. (2015), which involves a much larger number of repetitions than the other datasets.

For Davis-Stober et al. (2015), the plot shows a larger number of inconsistencies than in other cases (Fig. 1, top-right). This is because the consistency requirement is very stringent, due to the large number of repetitions (24). As an illustration, the middle-left panel of Fig. 1 plots the same data defining choices for a pair to be consistent if strictly more than 75% of the choices (19 or more) were identical.

Agranov and Ortoleva (2017) and McCausland et al. (2020) included choices with a (transparently) stochastically dominated lottery, depicted as red diamonds in Fig. 1. The dummy Dominated in Table 1 shows that choices involving dominance present very high consistency, independently of utility differences, but, remarkably, the latter remains a significant predictor of choice consistency even when controlling for dominance.

5. Discussion

We have shown that decisions become more consistent as the difference in estimated utilities between the alternatives becomes larger. Of course, parametric utility estimation requires the choice of a possibly-arbitrary functional family of utilities, but our analysis remains unchanged for alternative specifications.

We conclude that strength of preference is one of the dimensions underlying choice consistency. Obviously, we do not claim it to be the only dimension. For example, transparent

1 Whether a utility difference is positive or negative in Fig. 1 is based on the first presentation of the stimuli (left minus right). This is because in Agranov and Ortoleva (2017) repetitions were identical. However, in the remaining works, presentations were randomized.

2 Unsurprisingly, the relation is weaker or absent if one uses expected values instead. See also Alós-Ferrer and Garagnani (2018).

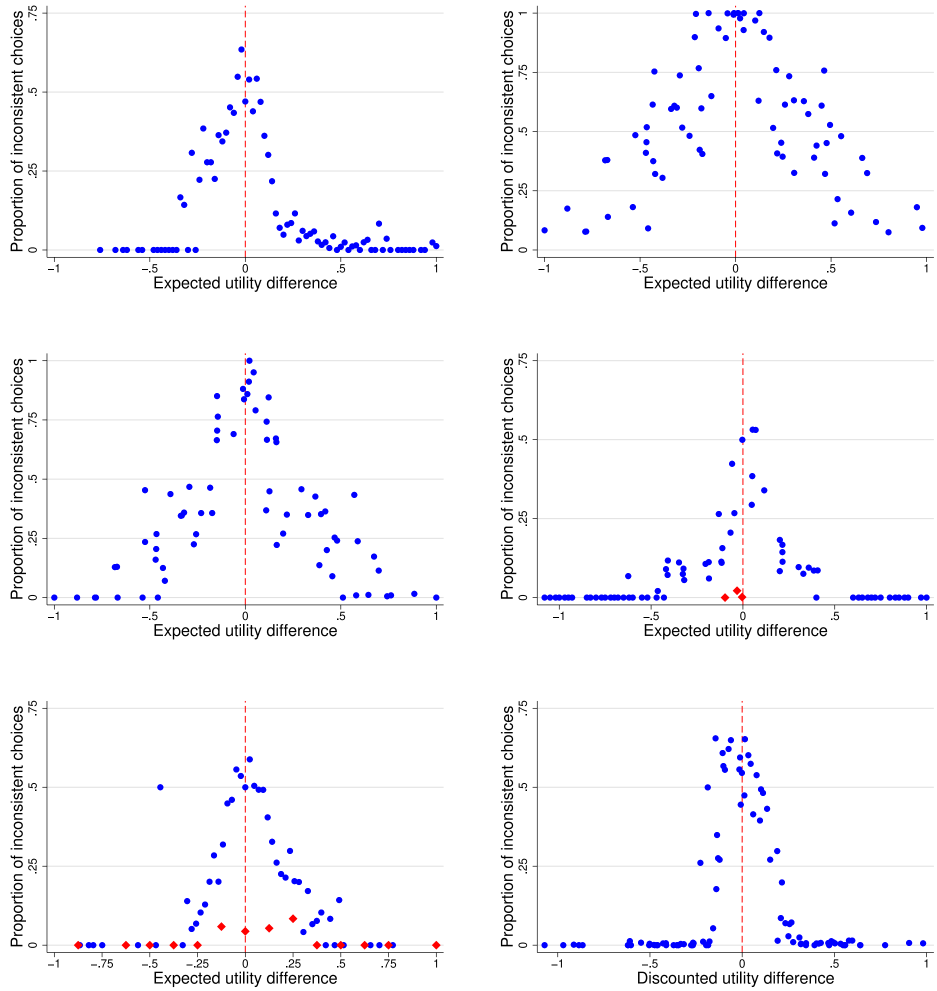

Fig. 1. Proportion of inconsistent choices as a function of utility differences across different datasets. Top-left: Hey (2001). Top-right: Davis-Stober et al. (2015), with the extreme definition of consistency (all choices equal). Center-left: Davis-Stober et al. (2015), with consistency defined as more than 75% identical choices. Center-right: Agranov and Ortoleva (2017). Bottom-left: McCausland et al. (2020). Bottom-right: He et al. (2019). Red diamonds (center-right and bottom-left) represent pairs involving stochastic dominance.

Table 1
Random effects probit regressions, probability of a consistent choice.

Consistent	Hey01	DSBC15	AO17	McCetal20	HGB19
Utility distance	4.924***	0.727***	4.157***	6.431***	5.950***
	(0.377)	(0.087)	(0.474)	(0.614)	(0.518)
Dominated			1.032***	1.292***	
			(0.219)	(0.080)	
Constant	−0.034	−5.609***	−0.894***	0.567***	0.457***
	(0.066)	(0.506)	(0.042)	(0.070)	(0.122)
N	5300	1200	800	1410	5340
Log Likelihood	−2163.021	−283.269	−1758.842	−5167.300	−1427.746
Wald test	170.85***	69.63***	90.81***	321.13***	131.70***

Notes: Hey01: Hey (2001). DSBC15: Davis-Stober et al. (2015). AO17: Agranov and Ortoleva (2017). McCetal20: McCausland et al. (2020). HGB19: He et al. (2019). Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

dominance clearly reduces inconsistency independently of utility differences. However, the evidence shows that utility differences play an important role for choice consistency in economic decisions, as predicted by discrete choice models McFadden (1974, 2001). These results also support stochastic choice models linking utilities and choice probabilities (e.g., Debreu, 1958; Luce, 1959), which is in contrast with the neoclassical view of ordinal preferences and deterministic choices (Hicks and Allen, 1934).

The implications of this research are twofold. First, data taking into account the relation between inconsistency and strength of preference could potentially be used to complement the literature that aims to distinguish between alternative models of stochastic choice (e.g., Buschena and Zilberman, 2000; Rieskamp, 2008), but which generally does not rely on repeated choices. Second, the results suggest that high levels of noise in decisions under risk might sometimes be due to the use of similarly-valued options. For instance, this observation might be of relevance for the literature on the elicitation and stability of risk preferences (Frey et al., 2017; Schildberg-Hörisch, 2018; Garagnani, 2020), as the amount of noise elicited by a method will be a function of the set of choices it relies on.

Acknowledgments

M.G. gratefully acknowledges the support of a Marlene Porsche Foundation scholarship, Switzerland for his PhD studies. We thank all authors of the papers for which the original datasets were collected for making them available.

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